

Optimal Allocation and Capacity Determination of Energy Storage Systems Within Active Distribution Networks Utilizing an Enhanced Sparrow Search Approach

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Abstract

Energy storage systems are pivotal in enhancing the low-carbon footprint and operational stability of active distribution networks. The paper introduces a novel approach for the intentional placement and capacity determination of energy storage devices within active distribution networks, highlighting the integration of carbon trading mechanisms. A robust optimization framework is developed to minimize active power losses, voltage deviations, and overall network costs while incorporating a tiered carbon trading model to assess its economic implications on the active distribution network's financial landscape.

Enhancements to the sparrow search algorithm are implemented in this study by incorporating chaotic initialization, sine-cosine mapping, and Levy flights, which augment the algorithm's diversity and capacity for comprehensive exploration. This refinement aims to strengthen the optimization process. This refinement leads to the development of a multi-objective optimization algorithm that leverages an advanced version of the sparrow search methodology. Which employs a Pareto front to conduct a more detailed and sophisticated investigation of the potential solution landscape.

The energy storage system's optimal layout within the active distribution network is determined by applying the Evidence Weighted Medi (EWM) approach in combination with the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). Experimental outcomes indicate that the refined algorithm significantly boosts the precision and effectiveness of the solution outcomes set. Moreover, the energy storage configuration, optimized with consideration of carbon trading, is crucial for promoting renewable energy integration and substantially reducing active power losses and voltage fluctuations in the network.

Keywords: Flexible loads; virtual power plant; prosumer; operation cost; default risk

1. Introduction

Addressing the "3060" carbon goals, China is transitioning its conventional power infrastructure towards a model that emphasizes sustainability, reduced carbon footprint, and smart management. This evolution is steering the power sector into a new epoch defined by its clean and low-carbon attributes, as well as its focus on safety and efficiency, with a pronounced emphasis on integrating renewable energy sources [1]. Amidst a sustainable energy framework, energy storage serves as a manageable asset that is pivotal for enhancing the flexibility of distribution networks, thus supporting a stable and rapid evolution of the power system. Presently, economic considerations are the predominant limitations affecting the implementation of energy storage solutions. The high initial investment and the extended timeframe for return on investment present significant economic challenges that impede the widespread adoption of energy storage within active distribution networks. These financial barriers can partially restrict the implementation scale of energy storage technologies in these networks. Identifying the optimal energy storage configuration is of paramount importance, as is determining the most efficient capacity allocation. Such strategic decisions are instrumental in curtailing the capital expenditure associated with energy

storage deployment. Through the refinement of these variables, the resilience of the distribution network's operations can be markedly strengthened. Such initiatives align with the overarching objective of bolstering the incorporation and application of energy storage technologies across the electricity industry.

Incorporating distributed energy resources and adaptable loads into the distribution network complicates the optimal scheduling of active distribution networks. To address this complexity [2]. In the realm of active distribution networks, the incorporation of robust protective mechanisms, adaptable network topologies, and sophisticated intelligent monitoring systems are essential for enhancing governance over dispersed energy resources and pliable consumption patterns. The contemporary power grid is witnessing a significant increase in the input from renewable energy sources. The extensive interfacing of these energy sources with the power grid, combined with the deployment of power electronic devices, presents considerable challenges to the preservation of the electrical system's stability and reliability. The grid is densely populated with a variety of loads, both critical and non-critical, necessitating a higher level of power quality. At peak demand times, the likelihood of load shedding is heightened due to the limited capacities of the system's transmission and distribution networks [3]. To mitigate the financial ramifications for consumers stemming from grid outages or blackouts, bolstering the system's dependability through the strategic deployment of distributed energy storage units is vital. These units serve as emergency or backup power sources, thereby circumventing the high economic outlay associated with scaling traditional transmission and distribution infrastructure, especially when the electrical load is typically below or near the rated capacity for the majority of the year [4]. Additionally, the progressive integration of distributed energy storage systems can alleviate the grid's electricity capacity shortfall during periods of heightened demand [5].

This methodology serves to enhance the network's resilience and concurrently refines operational efficacy, offering a supple cushion against fluctuations in both the generation and consumption of electricity.

A significant body of scholarly research has been dedicated to exploring the most effective placement and capacity determination of energy storage systems within active distribution networks. The scholarly work in this domain can be categorized based on the optimization objectives they target, distinguishing between single-objective approaches, which focus on a single performance metric, and multi-objective strategies, which consider a comprehensive set of performance criteria. Scholarly works denoted as [6] and [7], have indicated that the economic advantages of energy storage from the user's perspective are predominantly demonstrated through various application scenarios, including peak and off-peak load balancing, demand side management, participation in demand response programs, and provision of emergency power. The financial viability of energy storage solutions is significantly influenced by policy frameworks; Therefore, thoughtfully designed policies can efficiently guide the strategic allocation of energy storage resources by users.

To bolster the economic feasibility of energy storage systems, the study referenced in [8] has developed a mathematical framework utilizing sensitivity analysis for determining the ideal positioning and sizing of dispersed energy storage units. This model is instrumental in formulating an optimization plan that potentially substitutes traditional distribution network enhancement investments with distributed energy storage solutions.

The minimization of losses within an active distribution network continues to be a focal point of research. The research documented in [9] has explored the impact of distributed energy storage on reducing such losses, clarifying the concepts of integrating energy storage nodes and the strategies for their capacity assignment.

Furthering this discourse, the study in [10] has optimized the allocation of energy storage capacities with a dual focus on economic viability and the enhancement of voltage quality. Addressing the aspect of power supply reliability, the solutions proposed in [11] are particularly noteworthy. In regions where an elevated level of power supply reliability is mandated, a distributed energy storage system is commonly deployed as an uninterruptible power source. Such systems are designed to ensure that they can initiate a response within milliseconds in the event of a power outage, thereby solidifying the reliability of the power supply.

Swarm Intelligence Algorithms constitute an advanced category of optimization techniques, predominantly utilized for addressing intricate challenges, encompassing combinatorial, constrained, and multi-objective optimization scenarios. These methodologies are inspired by occurrences in nature or alternative realms of

solution-seeking, employing mechanisms akin to natural evolution and collective behavior to identify solutions that are either optimal or approximate the optimality threshold. When applied to optimization issues specific to engineering, these algorithms exhibit a robust capacity for logical problem resolution.

Reference [12] introduces an enhanced sparrow search algorithm for microgrid energy management, incorporating a superior reverse learning tactic and a variant of the firefly algorithm approach, which efficiently mitigates the risk of premature convergence. However, there is a need for further enhancement in the velocity and precision of the optimization outcomes. Consequently, the study reported in [13] introduced an advanced bare-bones particle swarm optimization (BBPSO) approach to address the challenges in DNA sequence design. This approach employed a dynamic lens-based method to initialize a high-quality solution set. It employed an innovative distance metric based on the signal-to-noise ratio to fine-tune the positioning of particles within the search space. Ultimately, a weed optimization strategy was proposed to eliminate subpar solutions, thereby enhancing the search efficiency. This methodology significantly bolstered the optimization speed. Experimental results indicated that the resulting DNA sequences were of superior quality. Reference [14] introduced a probabilistic elite learning approach to enhance the upper and lower-tier particles in Particle Swarm Optimization (PSO), effectively tackling large-scale optimization challenges. Still, this method will greatly increase the power requirements of the algorithm. Literature [15] created an optimization scheme for multi-objective optimization by building a PSO-ACO model with a lower-level model composed of A* algorithms. In reference [16], the investigators enhanced the Golden Eagle optimization algorithm's capacity for exploration through the introduction of a dual learning mechanism. Subsequently, this refined algorithm was applied to ascertain the optimal siting and sizing of energy storage systems, confirming its effectiveness. A study [17] introduced a multi-swarm Social Spider Algorithm (SSA), reducing the likelihood of a single swarm converging too soon on less-than-ideal solutions. The approach integrated a technique for exchanging weighted centroids with a dynamic, dimension-targeted reverse learning strategy to enhance the algorithm's precision in converging. The study reported in [18] proposes a dynamically adaptive sine-cosine fitness-augmented gray wolf optimizer for the precise adjustment of antenna hyperparameters. The efficacy of this algorithm in antenna optimization is validated through its application to the parameter adjustment of a dual T-shaped antenna configuration. In the work reported by [19], adaptive chaos mapping coupled with inverse learning is employed for the random initialization of the Social Spider Algorithm (SSA). This approach aims to generate an initial population that is more diverse and of higher caliber. Subsequently, the incorporation of dynamic inertia weights along with adaptive spiral strategies is utilized to enhance the algorithm's convergence speed and precision in subsequent stages. A study [20] proposes a dynamically adaptive sine-cosine fitness-based gray wolf optimizer for fine-tuning antenna hyperparameters. The algorithm's proficiency in antenna optimization is evidenced by its application to the parameter refinement of a dual T-shaped antenna. Concurrently, [21] presents an integrated approach that combines Particle Swarm Optimization (PSO) with the Social Spider Algorithm (SSA). This synergistic approach leverages the strengths of both PSO and SSA to bolster the algorithm's comprehensive exploration prowess and incorporates an elite reverse learning approach intended at generating a superior population of individuals.

The SSA, introduced in 2020, is an innovative swarm heuristic optimization algorithm. It emulates the collective behavioral patterns of a sparrow flock, particularly their strategies for hunting and evading detection. It can improve the relevant parameters for a specific environment, thus making the optimization problem more efficient. Because of its simple implementation and good convergence speed, SSA has been adopted in recent years to deal with various engineering optimization problems successfully.

In [22], the population of sparrows is initialized to achieve higher-quality solutions by incorporating a set of optimal points. The algorithm then integrates the brood strategy from Cuckoo Search (CS) during the exploration phase to enhance its global search capability. Finally, it employs Levy flights and Brownian motion to assist the algorithm in escaping local optima. The algorithm's effectiveness is subsequently demonstrated through its application to the Traveling Salesman Problem (TSP), thereby confirming its practical applicability. However, this method obtains better quality solutions while also introducing the set of good points and the spawning strategy will increase the algorithm's complexity because additional computations are needed to select and evaluate the good points and adjust the parameters of the spawning strategy. Accordingly, the study referenced in [23] introduces an enhanced sparrow search algorithm utilizing a fitness-distance balance (FDB) approach,

incorporating predatory strategies from Harris Hawk Optimization (HHO), and embedding Levy flights within the position adjustment mechanism for followers. This enhancement aims to bolster the algorithm's capacity to evade local optima. The FDB strategy is then integrated into the SSA for validation purposes. The findings indicate that while the algorithm shows effectiveness, there is a trade-off in terms of search efficiency. Meanwhile, [24] addresses the efficiency and convergence velocity of the sparrow search algorithm by conducting a neighborhood exploration around the fittest individuals to broaden the search scope and by applying differential evolution to the finder's position to expedite convergence. The Multi-Objective Sparrow Search Algorithm (MOSSA) originates from the foundational Sparrow Search Algorithm (SSA), preserving its simplicity, ease of implementation, and rapid convergence characteristics. In [25], the authors put forth an enhanced discrete sparrow search algorithm that employs a roulette initialization technique. The algorithm utilizes a sequential decoding approach for the advancement of sparrow position updates and incorporates Gaussian mutation along with an exchange operator to foster a more balanced exploration and exploitation. The integration of the 2-opt local search strategy further refines the performance. However, this addition raises the computational demands as it necessitates intricate local searches in every iteration, potentially diminishing the algorithm's efficiency. The algorithm's efficacy was confirmed through its application on 34 TSP benchmark datasets. Consequently, the investigations referenced in [26] and [27] have each formulated a multi-objective discrete Sparrow Search Algorithm aimed at addressing the dynamic reconfiguration issue within active distribution networks. Additionally, a dual-file maintenance-based multi-objective sparrow algorithm has been developed for power flow optimization challenges.

Building upon the aforementioned research endeavors, the present study introduces an optimization framework for energy storage systems within active distribution networks, integrating a tiered carbon trading mechanism. The objective is to attenuate active power losses, curtail voltage deviations, and reduce overall expenses. Accordingly, the Sparrow Search Algorithm has been enhanced by integrating the Chaos-Positive Cosine Algorithm and the Levy Flight Strategy, which augments its search performance and diversity. Additionally, the utilization of the Pareto solution set, in conjunction with the Information Entropy-TOPSIS method, aids in identifying a well-rounded solution that aligns with the multi-dimensional objectives of optimizing energy storage within active distribution networks.

2. A two-stage pricing model for a virtual power plant considering source-load uncertainty

The intentional placement, sizing, and operational strategies for energy storage systems within dynamically active distribution networks are essential for ensuring the economic feasibility and operational reliability of the electrical grid. To begin with, energy storage facilities, capable of functioning as both generators and consumers, when optimally located and sized, can significantly improve the voltage levels throughout the active distribution network. This strategic placement improves grid reliability and mitigates the capital outlay associated with energy storage infrastructure. Additionally, Energy storage systems are capable of significantly reducing the variability and uncertainty inherent to renewable energy sources, such as wind and solar power. Their superior modulation capabilities can also curtail active power losses within the distribution network, thereby augmenting the economic efficiency of grid operations. Figure 1 provides a diagrammatic depiction of an active distribution network, demonstrating the integration of distributed generation units like solar panels and wind generators, an energy storage facility, and the load profile of the network.

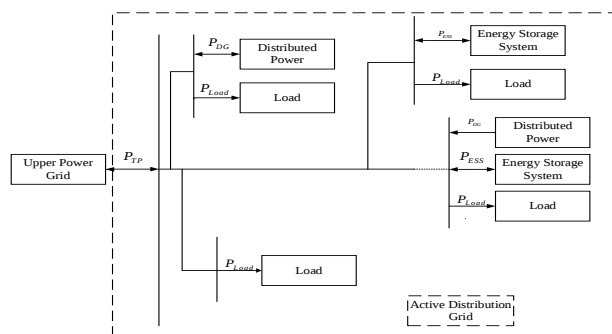


Fig.1 Active Distribution Grid Architecture

3. Internal Pricing Model for Virtual Power Plants Considering Source Load Uncertainty

A Carbon trading mechanism

China's current approach to allocating initial carbon emission quotas is based on the gratuitous quota method, where the allocation is linked to the system's power generation potential. The equation dictating the initial distribution of these complimentary carbon emission allowances for trading is outlined below:

$$C_A = \lambda_C \sum_{t=1}^T P_L(t) \quad (1)$$

Where: C_A is the system carbon emission quota; λ_C is the baseline value of the carbon emission right quota; T signifies the accounting interval for carbon trading fees. The notation $P_L(t)$ denotes the total load requirement of the active distribution network at time t .

As opposed to traditional carbon trading systems, a tiered carbon trading mechanism broadens the price range by implementing a stratified pricing system. This approach incentivizes the distribution grid to minimize its electricity procurement from upstream grids, thereby leveraging the system's inherent potential for the reduction of carbon emissions. Although the functioning of new energy generation sources and energy storage systems does not directly generate carbon emissions, indirect carbon emissions may arise from the interactions between the distribution grid and upstream grids. Consequently, the actual carbon emission formula for the distribution network is delineated as follows.

$$C_{TC} = \sum_{t=1}^T \left[a_1 + b_1 P_{TP}(t) + c_1 (P_{TP}(t))^2 \right] \quad (2)$$

Where: C_{TC} is the actual carbon emissions from the higher-level grid interaction; $P_{TP}(t)$ represents the power exchange with the higher-level grid at time t ; a_1 , b_1 , c_1 respectively, is the upper grid thermal power unit power supply carbon emission coefficients.

The actual carbon emissions from the distribution grid C is given by.

$$C = C_{TC} - C_A \quad (3)$$

The stepwise carbon transaction cost-free model f_c is as follows.

$$f_c = \begin{cases} c_{CO_2} \cdot C, & C \leq \tau \\ c_{CO_2} (1 + \sigma)(C - \tau) + c_{CO_2} \cdot \tau, & \tau < C \leq 2\tau \\ c_{CO_2} (1 + 2\sigma)(C - 2\tau) + c_{CO_2} (2 + \sigma)\tau, & 2\tau < C \leq 3\tau \\ c_{CO_2} (1 + 3\sigma)(C - 3\tau) + c_{CO_2} (3 + 3\sigma)\tau, & 3\tau < C \leq 4\tau \\ c_{CO_2} (1 + 4\sigma)(C - 4\tau) + c_{CO_2} (4 + 6\sigma)\tau, & 4\tau < C \end{cases} \quad (4)$$

Where: c_{CO_2} for the base price of laddered carbon trading; τ represents the duration of the carbon emission interval; σ denotes the rate of price escalation; f_c is the cost of laddered carbon trading.

In the conventional distribution network paradigm, electricity is supplied to meet demand primarily through thermal generation assets connected to the upstream grid. Nevertheless, as renewable energy sources are incorporated into the distribution network, there is a notable transition towards supplying clean energy. This integration not only diminishes the reliance on electricity procured from the upstream grid but also results in reduced costs associated with power acquisition and carbon emissions. Moreover, the distribution network can generate revenue by selling its unutilized carbon emission allowances.

The variable nature of renewable energy sources such as wind and solar poses challenges to grid stability. Without strategic deployment of energy storage systems, periods of high renewable energy generation may lead to unnecessary energy loss. Commonly referred to as "wind and light" abandonment. Theoretical models suggest that an energy storage system if optimally configured for high storage and low discharge rates, can significantly

enhance the consumption of renewable energy. Consequently, this can lead to reduced carbon emissions within the distribution network by minimizing reliance on carbon-intensive power sources.

B Target function

The active distribution network has been engineered with the goal of reducing active network losses, voltage deviations, and overall system costs. To realize these objectives, an encompassing multi-objective model for the positioning and capacity determination of energy storage installations has been developed. The essence of this optimization model is encapsulated as follows:

$$\begin{cases} F = \min[F_1(x), F_2(x), F_3(x)] \\ h(x), 0 \\ \text{s.t. } g(x) = 0 \end{cases} \quad (5)$$

Where: F is the total optimization objective; x is the feasible solution of the decision variable; The functions $g(x)$ and $h(x)$ represent the model's constraints, with equality and inequality constraints, respectively.

The active distribution network active network loss F is formulated as follows.

$$F_1 = \sum_{i=1}^{24} \sum_{j \in M_L} (G_{ij}[U_i^2(t) + U_j^2(t) - 2U_i(t)U_j(t)\cos\delta_{ij}(t)]) \quad (6)$$

Where: The voltage magnitudes at node i and node j at time t are represented by $U_i(t)$ and $U_j(t)$, respectively. G_{ij} is the conductance of $i - j$ branch; The phase angle difference between the voltages at node i and node j at time t is denoted by $\delta_{ij}(t)$; M_L is the set of network nodes.

The voltage deviation index, labeled as F_2 , is utilized to evaluate the operational reliability of the distribution network, with its definition provided by the following equation.

$$F_2 = \sum_{t=1}^{24} \left\{ \sum_{i=1}^{N_{Bus}} \left[\frac{U_i(t) - U_i^{\exp}}{\Delta U_i^{\max}(t)} \right]^2 \right\} \quad (7)$$

Where: N_{Bus} represents the aggregate count of nodes within the system; The voltage amplitude at node i at time t is denoted by $U_i(t)$; $\Delta U_i^{\max}(t)$ represents the upper limit of acceptable voltage deviation at node i at time t .

The total expense of an active distribution network encompasses the cost of the energy storage system, denoted as f_{ESS} , the costs linked to the procurement of power from the primary grid, denoted as f_{TP} , and the expenses associated with tiered carbon trading, denoted as f_C , with the following correspondences.

$$F_3 = f_{TP} + f_{ESS} + f_C \quad (8)$$

The expenses encompassed by an energy storage system comprise capital expenditure, denoted as f_{Inv} , along with operational and maintenance costs, denoted as $f_{O\&M}$:

$$\begin{cases} f_{ESS} = f_{Inv} + f_{O\&M} \\ f_{Inv} = \sum_{i=1}^{N_{ESS}} [(C_E E_{ESS,i} + C_P P_{ESS,i})] \cdot \frac{r(1+r)^{T_i}}{(1+r)^{T_i} - 1} \\ f_{O\&M} = \sum_{i=1}^{N_{ESS}} \sum_{t=1}^{T_i} a_i (C_E E_{ESS,i} + C_P P_{ESS,i}) \end{cases} \quad (9)$$

Hereby: N_{ESS} signifies the quantity of energy storage systems installed; C_E and C_P represent the cost per unit of capacity and power for energy storage, respectively; E_{ESS} and P_{ESS} denote the installed capacity and power of the $i - th$ energy storage system; T_i indicates the operational lifespan of the $i - th$ energy storage system; a_i is the

coefficient for operation and maintenance costs associated with the $i - th$ energy storage system; and γ stands for the discount rate.

The expense for power interaction with the higher-tier grid is:

$$f_{TP} = \sum_{t=1}^T C_{TP} \cdot P_{TP}(t) \quad (10)$$

What does the distribution network's per-unit interaction tariff with the higher-level grid amount to?

C Constraints

1) The distribution grid power balance constraints are:

$$\sum_{i=1}^{N_w} P_{Wind,i}(t) + \sum_{i=1}^{N_{PV}} P_{PV,i}(t) + P_{TP}(t) = \sum_{i=1}^{N_L} P_{Load,i}(t) + \sum_{i=1}^{N_{ESS}} P_{ESS,i}(t) + P_{Loss}(t) \quad (11)$$

Hereby: N_w denotes the total count of wind power stations integrated into the system; N_{PV} signifies the total count of photovoltaic power stations within the system; N_L denotes the total count of load points within the system; $\sum_{i=1}^{N_L} P_{Load,i}(t)$ is the power of the network load point at the moment t ; $P_{Loss}(t)$ represents the amount of power lost in the network at time t .

2) The energy storage system constraints are:

$$\begin{cases} -P_{ESS}, P_{ESS}(t), P_{ESS} \\ SOC_{min}, SOC(t), SOC_{max} \\ E_{ESS}(t) = E_{ESS}(t-1) + P_{ESS}(t) \cdot \eta_C \\ E_{ESS}(t) = E_{ESS}(t-1) - P_{ESS}(t) / \eta_{Dis} \\ (S_{ESS,i} \in M_L) \cap (S_{ESS,i} \neq S_{Grid}) \end{cases} \quad (12)$$

In this context: P_{ESS} refers to the nominal power capacity of the energy storage system; SOC_{min} and SOC_{max} represent the lower and upper bounds. Correspondingly, to prevent excessive charging and deep discharging of the energy storage system, the State of Charge (SOC) is restricted to a range between 0.1 and 0.9. Moreover, to maintain the consistent operation of the energy storage, the SOC is set to 0.5 at the beginning and end of each operational cycle. The efficiency of charging and discharging for the $i - th$ energy storage unit is denoted by η_C and η_{dis} , respectively; $S_{ESS,i}$ denotes the installation node of the $i - th$ energy storage unit within the system; S_{Grid} denotes the connection point between the distribution network and the primary power grid, with energy storage facilities capable of being installed at any node other than the connection point.

3) The upper grid interaction power constraints are:

$$P_{TP}^{min}, P_{TP}(t), P_{TP}^{max} \quad (13)$$

Where: P_{TP}^{max} and P_{TP}^{min} are the interacting power's upper and lower limits, respectively.

4) The active distribution network's current constraints are as follows.

$$\begin{cases} Q_i = U_i \sum_{j=1}^{N_{Bas}} U_j (G_{ij} \sin \delta_{ij} + B_{ij} \cos \delta_{ij}) \\ P_i = U_i \sum_{j=1}^{N_{Bas}} U_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \\ U_i^{min}, U_i, U_i^{max} \end{cases} \quad (14)$$

Where: B_{ij} is the electrician of $i - j$ branches; U_i^{max} and U_i^{min} represent the upper and lower limits of acceptable voltage at node i , respectively.

4. Improved multi-objective sparrow search algorithm

A Standard sparrow algorithm

Within this research, the optimal allocation model for energy storage is depicted as being of high dimensionality and, a non-linear optimization challenge. Given the intricate nature of conventional solution techniques, this issue is commonly tackled using optimization algorithms that leverage swarm intelligence. The Sparrow Search Algorithm, motivated by the collective hunting strategies of sparrows, excels at traversing these intricate problem domains. It leverages a division of labor among explorers, followers, and warners to efficiently identify optimal solutions. This approach shows better performance when it comes to how quickly it converges and how steadily accurate it remains. It does better than other intelligent optimization methods. As a result, it has been used a lot to tackle a wide range of optimization problems.

The diagrammatic portrayal of the algorithmic structure presented in this study is illustrated in Figure 2, illustrating the structured approach to solving the energy storage allocation problem.

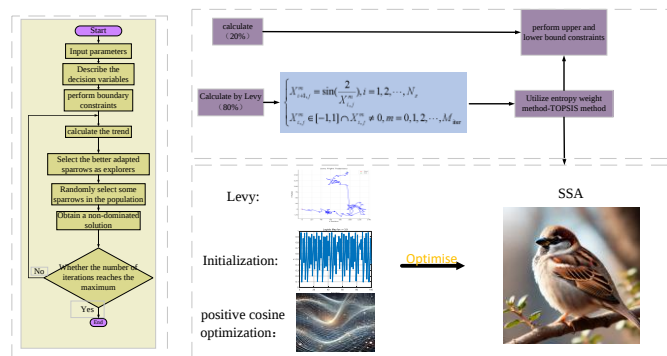


Fig.2 Algorithmic Framework

The location of the explorer is adjusted according to the subsequent formula:

$$X_{i,j}^{m+1} = \begin{cases} X_{i,j}^m \cdot \exp\left(\frac{-i}{K \cdot M_{iter}}\right), R_2 < ST \\ X_{i,j}^m + \beta \cdot L, R_2 \geq ST \end{cases} \quad (15)$$

Where: $X_{i,j}^m$ denotes the position of the $i - th$ sparrow in the j -dimensional space, with m representing the current iteration count; M_{iter} denotes the maximum iteration limit. K is the sparrow direction control parameter taking the value of $[-1,1]$ random numbers; The parameter β represents the sparrow's step size, which adheres to a normally distributed random variable. It is a $1 \times j$ matrix where each element is set to 1. The figures R_2 and ST denote the alarm limit and the safety limit, respectively.

The position of the follower is modified based on the subsequent equation:

$$X_{i,j}^{m+1} = \begin{cases} X_{Best}^{m+1} + |X_{i,j}^m - X_{Best}^{m+1}| \cdot A^+ \cdot L, \text{ other} \\ Q \cdot \exp\left(\frac{X_{Worst}^m - X_{i,j}^m}{i^2}\right), i > M_{iter} / 2 \end{cases} \quad (16)$$

Where: X_{Best}^{m+1} and X_{Worst}^m denote the positions of the sparrows possessing the highest and lowest fitness, respectively; Matrix A is of size $1 \times j$, comprising elements that are random integers of either 1 or -1, with the property that $A^+ = A^T(AA^T)^{-1}$.

The alert agent is capable of recognizing threats, abandoning the current position, and relocating to a novel one. For each generation, this alert agent is arbitrarily chosen from 20% of the total population, with the position update process detailed subsequently:

$$X_{i,j}^{m+1} = \begin{cases} X_{i,j}^{m+1} + \beta \cdot |X_{i,j}^m - X_{Best}^m|, & F_i > F_{Best} \\ X_{i,j}^{m+1} + K \cdot \left(\frac{|X_{i,j}^m - X_{Worst}^m|}{(F_i - F_{Worst}) + \varepsilon} \right), & F_i = F_{Best} \end{cases} \quad (17)$$

Where: F_i, F_{Best}, F_{Worst} denote the fitness values of sparrow i , the overall optimal fitness, and the overall worst fitness, respectively; ε denotes a small constant value.

B Improvement of the sparrow algorithm

The model's decision variables encompass the siting, capacity, and hourly charging/discharging schedules of energy storage facilities over a typical day, with the storage location being discrete. The intricate nonlinear model is subject to numerous constraints, leading to a slower search process. To tackle these challenges, this study enhances the Sparrow Search Algorithm, proposing an enhanced version as detailed subsequently.

- 1) The Sinusoidal chaos model is employed for the initial population assignment, enhancing the search diversity among the population.
- 2) The nonlinear adjustment factor, coupled with the sine-cosine algorithm's concept, is leveraged to bolster the explorer's global search capacity.
- 3) Enhance the follower's global search ability using the Levy flight search mechanism.

The Sin chaotic initialization strategy can be used to obtain a sufficient initial solution with uniform distribution in the search space, which can be articulated as follows.

$$\begin{cases} X_{i+1,j}^m = \sin\left(\frac{2}{X_{i,j}^m}\right), i = 1, 2, \dots, N_s \\ X_{i,j}^m \in [-1, 1] \cap X_{i,j}^m \neq 0, m = 0, 1, 2, \dots, M_{iter} \end{cases} \quad (18)$$

Where: The variables N_s signifies the count of sparrows, while N_d represents the dimensionality of the objective function. Each variable serves a distinct purpose within the model. Within the Sparrow Search Algorithm, as iterations accumulate, the explorer's search domain progressively narrows, potentially leading to local optimization issues; hence, a nonlinear adjustment factor, denoted as α , is incorporated. The algorithm integrates the sine-cosine approach to amplify the explorer's global search capacity during the initial phases of the search and to broaden the local search area in the later stages. The position update is executed as follows:

$$\alpha = \left(\frac{m}{M_{iter}} \right)^2$$

$$X_{ij}^{m+1} = \begin{cases} (1-\alpha) \cdot X_{i,j}^m + \alpha \cdot \sin(r_1) |r_2 \cdot X_{Best}^m - X_{i,j}^m|, & R_2 < ST \\ (1-\alpha) \cdot X_{i,j}^m + \alpha \cdot \cos(r_1) |r_2 \cdot X_{Best}^m - X_{i,j}^m|, & R_2 \geq ST \end{cases} \quad (19)$$

Where: The parameter r acts as a control step factor. It selects a random number uniformly distributed between 0 and 2π . This number acts as a weight that modifies how much the current best solution affects the position update of the explorer. Additionally, a uniformly distributed random value within the interval $[0, 2]$ is employed. The ensuing position adjustment for the followers, following the incorporation of the Levy flight strategy, is described below:

$$X_{i,j}^{m+1} = \begin{cases} Q \cdot \exp\left(\frac{X_{Worst}^m - X_{i,j}^m}{i^2}\right), & i > M_{itey} / 2 \\ X_{Best}^{m+1} + X_{Best}^{m+1} \otimes \text{Levy}(D_s), & \text{other} \end{cases} \quad (20)$$

where, $Levy(D_s)$ is the Levy computational formula.

Using the improved crowding method to eliminate the part of the external population with similar distances, we finally obtain a set of uniformly distributed and complete Pareto non-dominated solutions.

Solutions that are non-dominated within the external archive, ultimately yielding a comprehensive ensemble of evenly spread Pareto non-dominated solutions.

C Algorithm flow

Within the augmented multi-objective Sparrow Search Algorithm, the spatial positioning of each sparrow corresponds to the decision variables that are slated for optimization. The best fitness value corresponds to the most advantageous outcome of the objective function, and the placement of the energy storage system is determined by rounding within continuous space. The limitations imposed on the energy storage system, as articulated in Equation (12), are established initially. Following the initialization of the sparrow population's positions and their respective fitness values, the starting positions for energy storage installation, capacities, and hourly outputs are determined. Subsequently, using the parameters of the active distribution network, the time-sequence operational data is retrieved. The algorithm is then refined to iteratively update the sparrow population's positions and fitness values, yielding the energy storage's charging and discharging powers across 24 hours. The positions within the external archive are refreshed, the Pareto front of non-dominated solutions is refined, and these iterations continue until the predefined iteration cap is met. Eventually, a compilation of Pareto-optimal solutions is derived from the external archive. By employing the entropy weighting method in conjunction with the TOPSIS approach, an optimal decision-making framework for energy storage placement and capacity is determined. This encompasses the ideal sites for energy storage deployment, the necessary capacities, and the operational tactics for energy storage, with a comprehensive flowchart of the solution depicted in Figure 3.

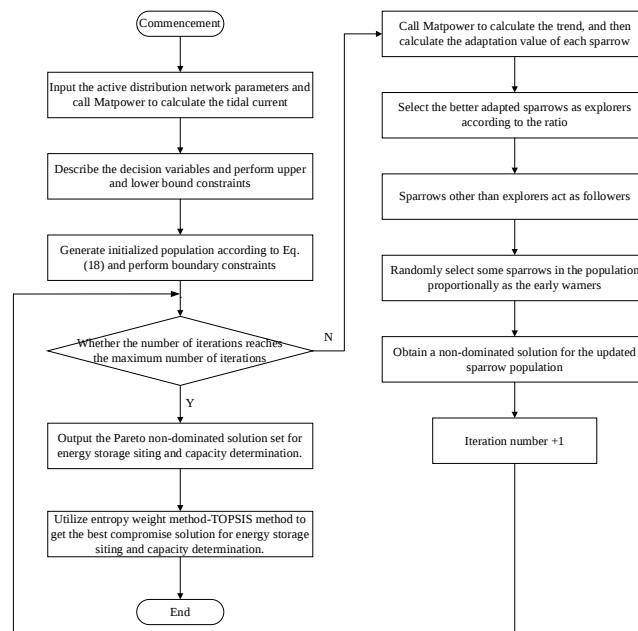


Fig.3 Active distribution network energy storage siting and capacity determination solution flow

5. Example Analysis

A Parameterization

For this investigation, an augmented IEEE-33 node distribution network is deployed as a simulation platform, functioning at a standard voltage of 12.66 kV. Nodes 20 and 30 are integrated with wind farms, each with a capacity of 2 MW, while nodes 6 and 16 are linked to photovoltaic installations, each with a capacity of 2.5 MW. Utilizing actual data from a location in Xinjiang, the typical daily generation profiles for wind and solar power are depicted in Figure 5. The aggregate network load is specified as 3.715 MW plus j2.3 MVar; the normalized

daily load curve and the time-based tariff curve are illustrated in Figures 6 and 7, respectively. Matlab 2022b software is leveraged for programming, and the Matpower toolkit is applied for power flow calculations. It is presupposed that two energy storage facilities are established, with the expense per kilowatt of energy storage's power set to 700 yuan/kW and the expense per kilowatt-hour of energy storage's capacity set to 1200 yuan/(kW·h). These energy storage systems possess a charging and discharging efficacy of 95%, a projected lifespan of 15 years, and a yearly discount rate of 0.06, accompanied by annual operation and maintenance charges at the rate of 0.5%. The power limits for the energy storage setups are designated as the upper and lower bounds of 90% and 10%, respectively, relative to the system's utmost total load power, with the thermal power generation units allocated to 0.5% of the system's peak total load power—the carbon emission coefficients about electricity generation. The specific parameters of the refined Sparrow Search Algorithm are presented in Table 1.

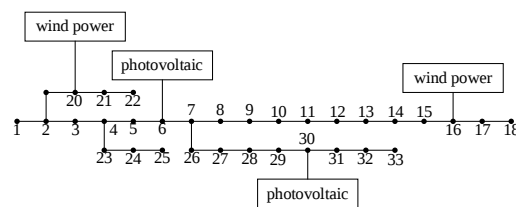


Fig.4 Improved IEEE33 node topology diagram

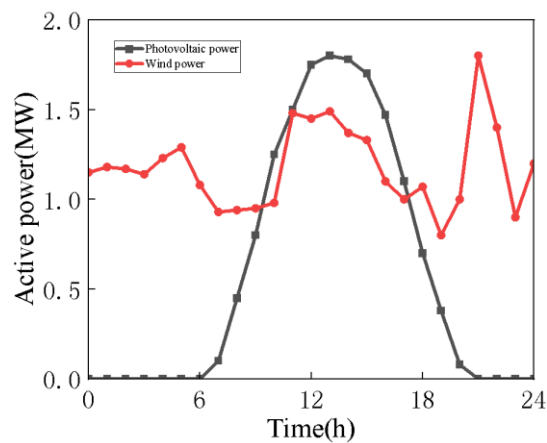


Fig.5 Typical daily characteristic curves of photovoltaic and wind energy

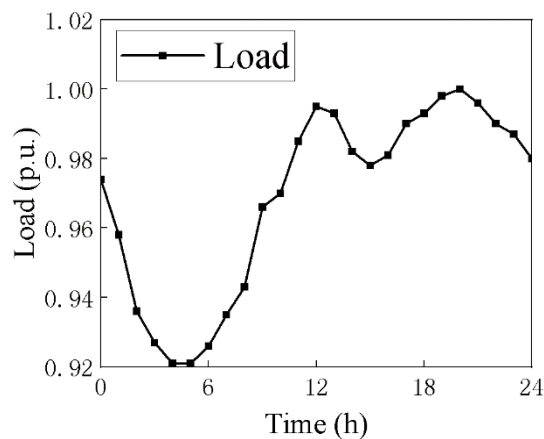


Fig.6 Typical daily load and time-of-day tariffs

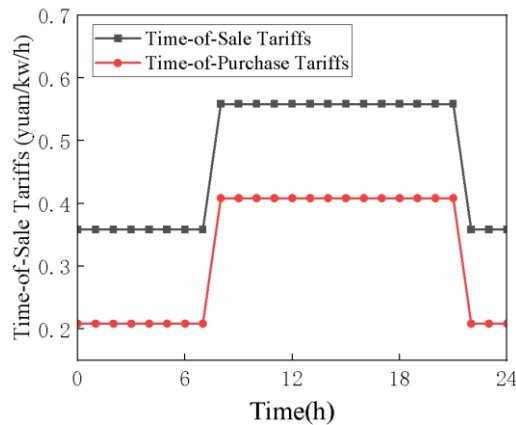


Fig.7 Typical daily time-of-day tariffs

B Analysis of optimization results

This manuscript constructs three comparative scenarios to substantiate the efficacy of the active distribution network energy storage optimization model that integrates carbon trading mechanisms. The outcomes of these optimizations are detailed in Table 2, with a detailed breakdown of the comprehensive costs associated with the distribution network presented in Table 3.

The scenarios are delineated as follows:

Scenario 1: This setup disregards the impact of carbon trading while maintaining all other parameters by the conditions outlined in this paper.

Scenario 2: This setup is by the approaches described in this study. The Sparrow Search Algorithm used in the solution strategy is augmented by Pareto optimal solutions to address the multi-objective optimization requirements. This context does not consider other algorithms that might expedite the enhancement strategy.

Scenario 3: This scenario presupposes a distribution network devoid of energy storage configurations, yet it adheres to all other conditions as stipulated in this paper.

These scenarios are meticulously designed to isolate the effects of carbon trading considerations and algorithmic enhancements on the optimization of energy storage within active distribution networks.

Table 1 Simulation parameter settings for the improved sparrow algorithm

Parameter name	Retrieve a value
Number of sparrows	100
Maximum iteration count	100
Alert threshold value	0.8
Proportion of explorers	0.6
Percentage of Early Warners	0.2
Pareto solution set size	100

Three comparative scenarios have been devised to validate the efficacy of the energy storage optimization model for active distribution networks that incorporate carbon trading mechanisms, with the detailed optimization outcomes presented in Table 2. Table 3 offers a granular analysis of the total expenses associated with the distribution network.

The specific programs set are as detailed below.

Scenario 1: The model does not consider carbon trading, and other conditions are consistent with this paper.

Scheme 2: the model is consistent with the scheme in this paper, the sparrow algorithm used in the solution algorithm is only improved by the Pareto optimal solution to adapt to the multi-objective optimization, and other algorithms are not considered to accelerate the improvement strategy.

Scenario 3: The energy storage configuration is not considered, and other conditions are consistent with this paper.

Table 2 Optimization results of energy storage for different scenarios

Programmatic	Access points	Power /MW	Capacity/MWh	F ₂ /p.u.	F ₁ /MW	F ₃	Solving time
Programmatic 1	9	0.485	0.89	1.78	3.22	101.0	94.58
	24	0.516	1.02				
Programmatic 2	11	0.670	1.69	1.14	2.94	115.0	182.26
	28	0.861	1.34				
Programmatic 3	—	—	—	2.45	4.38	37.5	72.32
		—	—				
Scenario	12	0.651	1.63	1.13	2.81	106.8	112.31
	28	0.838	1.29				

As depicted in Table 2, the outcomes of Scheme 2 align with the findings of this study. The accuracy of the refined Sparrow Search Algorithm is slightly better compared to its original version, indicating that both the modified and unmodified versions are capable of achieving the optimal solution. Still, there is a significant difference in the efficiency of the solution. The refined approach employed within this study substantially boosts the optimization performance, enhancing the solution efficiency by 38.4%.

Scheme 1 does not incorporate a carbon trading mechanism, thus failing to ensure the optimization of renewable energy utilization; however, the energy storage system is effective in enhancing renewable energy consumption. Consequently, the storage capacity configured in Scheme 1 is relatively reduced, and the configuration of the energy storage cost is also lower. Nevertheless, Scheme 1 has not fully utilized the new energy power, leading to a comparatively higher cost for interactive power. Both Scenario 2 and the scenario presented in this paper incorporate a carbon trading mechanism to encourage the maximization of renewable energy utilization. The node for energy storage deployment is linked to the point of new energy. In terms of optimization goals, In Scenario 3, the absence of an energy storage system configuration results in a slower uptake of renewable energy, sporadic wind power curtailment, and occasional deficits in wind power supply. The power balance is met solely through interaction with the upper grid, leading to the greatest voltage deviation and network losses in the system. The cost of interacting with the upper grid is also higher. However, due to savings on energy storage configuration costs, the total system cost index appears to be the lowest. This decrease in the overall cost index is due to the exclusion of the cost associated with the abandonment of wind power, if included, the total cost could be higher. Moreover, the omission of energy storage configuration not only poses security risks to the distribution network operations but also makes it challenging to address security concerns.

Table 3 Sub-costs of the integrated costs of active distribution network Units:k

programmatic	Energy storage system costs	Interactive power costs	Carbon trading costs
Programmatic1	76.3	24.8	—
Programmatic2	123.5	17.8	-26.3
Programmatic3	—	37.6	-2.1
Scenario	116.1	17.3	-26.3

Table 3 shows the comprehensive cost of the active distribution network, compared with this paper's program, program 1 does not take into account the carbon trading mechanism, so the optimization process of energy storage system operation can not fully take into account the maximization of renewable energy consumption, so there is a certain amount of abandoned wind and the light phenomenon of program 1, but the amount of abandoned wind and light is lower than that of program 3; the cost of interactive power in program 1 is higher than this paper's program but lower than that of program 3. The wind and light abandonment in programs 1 and 3 are shown in Fig.7, and the wind and light abandonment cost in program 1 is shown in Fig.7. The amount of wind and light discarded in Scheme 1 and Scheme 3 is shown in Fig.8.

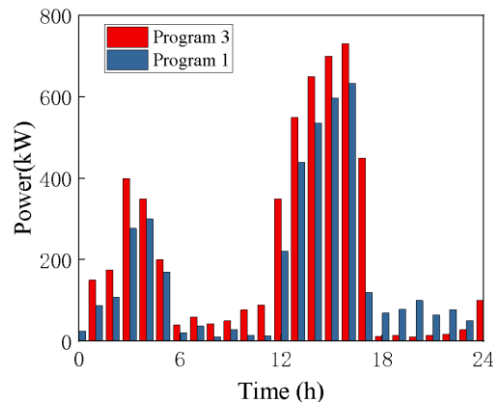


Fig.8 Amount of wind and light abandoned by the two scenarios

Scenario 2 and this paper's scenarios of wind and light abandonment are 0, the new energy to achieve complete consumption, scenario 3 and scenario 1 have wind and light abandonment phenomenon, In Scenario 3, due to the absence of energy storage system configuration, the curtailment of wind and solar power is more significant, with the total discarded power amounting to 5.02 MW and 4.03 MW for the two scenarios, respectively. The strategic operation of the storage system and its resultant State of Charge (SOC) trajectories, along with the optimized configuration across various nodes as presented in this study, are depicted in Figures 8 and 9. These figures, when considered alongside the typical daily patterns of wind, solar power, and load demands, offer insights into the system's performance. Observations indicate that the energy storage system situated at node 28 within the active distribution network is in proximity to the renewable energy plant when compared to the system at node 12, and exhibits greater charging and discharging capacities than the latter. Nonetheless, during operational phases, the charge level, or State of Charge (SOC), for the energy storage at node 28 varies within the interval of [0.1, 0.8], whereas the SOC for the node 12 energy storage oscillates between [0.45, 0.8].

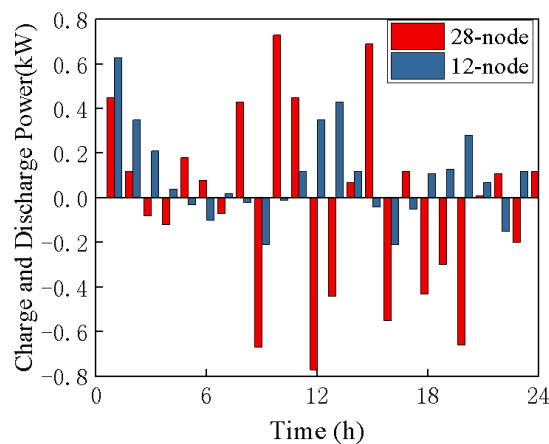


Fig.9 Operation strategy of 28-node and 12-node energy storage system

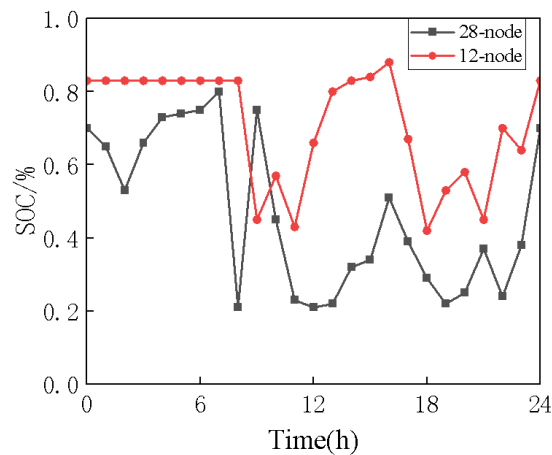


Fig.10 12-node and 28-node energy storage system SOC curve

The deployment of the energy storage system enhances the distribution of nodal voltages across the network. All node voltages are in the $[0.93, 1.05]$ range, and the node voltage containing the new energy power station has a certain improvement. This suggests that the renewable energy plant inherently contributes to the enhancement of network voltage levels. And to a certain degree, boosts the voltage profile. Energy storage systems are capable of stabilizing voltage distributions among nodes in the active distribution network by managing the charging and discharging processes. This capability, in turn, facilitates the use of renewable energy sources. Simultaneously, the energy storage system plays an essential role in sustaining stable voltage profiles across network nodes. Its effectiveness is evidenced by the system's ability to efficiently manage node voltages, ensuring overall network reliability. The energy storage system achieves this goal through its flexible charging and discharging mechanisms, which not only facilitate the incorporation of renewable energy but also enhance the overall stability and reliability of the network. This function underscores the dual benefits of energy storage: it promotes the uptake of renewable energy sources and maintains voltage stability within the active distribution network.

6. Conclusion

This study introduces an optimal energy storage allocation strategy incorporating carbon trading mechanisms. Develops a multi-objective optimization framework designed to minimize active network losses and voltage deviations, and implements the model resolution using the multi-objective ISSA algorithm. The study's conclusions are encapsulated below.

- 1) The implementation of a carbon trading mechanism is found to markedly enhance the uptake of renewable energy sources, thereby concurrently diminishing the carbon footprint of active distribution networks. This strategy is conducive to steering the evolution of these networks along a trajectory of low-carbon and environmentally benign growth. Nonetheless, it is observed that the overall system expenditure escalates as a consequence of the requisite allocation of energy storage resources. This increased cost is attributed to the integration and deployment of energy storage technologies, which, while essential for operational efficiency and carbon reduction objectives, introduce additional financial considerations into the system's economic calculus.
- 2) Energy storage systems are capable of substantially stabilizing voltages across nodes within the active distribution network, reducing active power losses, and also promoting the utilization of renewable energy sources.
- 3) The multi-objective enhanced Sparrow Search Algorithm, which incorporates chaotic initialization, cosine algorithms, and Levy flight strategies, not only improves the accuracy of the solutions but also markedly boosts the efficiency of the solution-finding process, thereby rendering the outcomes of energy storage optimization more rational.

As the pursuit of the "dual carbon" objectives gathers momentum, the variability of load demands across active distribution networks is expected to significantly impact the strategic placement of energy storage assets. As a

result, forthcoming studies will explore the implications of diverse load uncertainties on the most effective allocation of energy storage, aiming to provide a nuanced understanding of how varying load profiles can affect the planning and deployment of these critical assets.

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